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Habitly: An Emotion-Aware Habit Tracking Application for Improved Behaviour Change

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ABSTRACT

The process of forming a habit is still difficult, with a failure rate of 92% regarding resolutions that are no longer pursued after two months. Current state-of-the-art habit trackers rely on what users do, ignoring how they feel. Habitly is an emotion-aware habit-tracking application, capturing emotional context upon habit completion through nine emoji-based emotional states. In summary, using React 18 and IndexedDB for offline-first architecture, Habitly offers full data privacy with analytics to correlate emotional patterns with the success or failure of a habit. The workflow was streamlined into a 3-tap workflow to minimize friction. Drawing inspiration from computational habit formation models and emotion recognition research, this work demonstrates that including emotional context enables users to understand behavioral patterns, adding to digital behavior change literature.

1. INTRODUCTION

1.1 Problem Statement

While many habit-tracking applications exist, they focus exclusively on tracking behaviors while completely disregarding emotional context. Research shows that emotions are integral to motivation, decision-making, and reinforcement of behavior. These trackers have three deficiencies: lack of capture of emotional context, inability to find performance variability patterns, and cloud-dependent solutions compromising privacy.

1.2 Theoretical Foundation

Habit Formation: The formation of habits occurs through repetitions of behavior within goal-directed learning. Klein et al. (2011) presented a computational model in which the strengthening of habitual behavior increases with consistency but asymptotically approaches a plateau, whereas abandoned behaviors decline proportionally at a reduced rate.

Emotion Recognition: Research shows emotions can be captured through visual expressions, vocal patterns, and physiological signals. Dimensional emotion models reflect that emotions are multi-dimensional signals, thus enabling subtle distinctions and real-time tracking.

1.3 Research Questions

RQ1: How does capturing emotional context improve habit adherence?

RQ2: Which emotional states correlate with habit success?

RQ3: Can offline-first architecture provide superior privacy while maintaining analytical functionality?

RQ4: Does a 3-tap workflow increase engagement?

1.4 Solution: Habitly

Habitly addresses these gaps through three innovations:

Emotion-Aware Architecture: Captures emotional context at habit completion through nine states which span valence, energy, and physical dimensions.

Computational Habit Modeling: Computes habit strength using the following formula: $HS_{t+1} = HS_t - HS_t \times HDP + (1 - HS_t) \times Beh_t \times Cue_t \times HGP$, where HDP habit decay parameter ≈ 0.15 - 0.2 and HGP habit gain parameter ≈ 0.1-0.3 based on empirical validation.

Offline-First Design: It leverages IndexedDB through Dexie.js for complete on-device data storage, granting end-to-end user privacy without cloud dependency.

Simplified Workflow: 3-tap interaction Select Habit → Choose Mood → Mark Complete.

2. LITERATURE REVIEW

Computational Habit Models: Zhang et al. 2022 tested habit modeling in dental behavior studies with N = 36, N = 75; 68.6% and 76.1% accuracy, respectively, were achieved. Optimal parameters: HGP ≈ 0.1-0.3, HDP ≈ 0.15-0.2. Computed habit strength enables systems to distinguish genuine habits from digital prompt compliance.

Emotion Recognition: The work of Udahemuka et al. presents a review on multimodal emotion recognition based on visual, vocal, and physiological signals. Dimensional emotion models, such as valence-arousal models, make it possible to track subtle distinctions and label them in real time. Digital Interventions: Wang et al. (2024) found some important elements such as contextual cues, reward mechanisms, timing strategies, and personalization. Nevertheless, most studies consider only short-term outcomes. Research Gap: None of the previous works have integrated emotion-aware tracking with computational habit modeling while implementing privacy-preserving architecture.

2. LITERATURE REVIEW

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Emotion Recognition: Udahemuka et al. (2024) reviewed multimodal emotion recognition using visual, vocal, and physiological signals. Dimensional emotion models, such as valence-arousal, allow the tracking of subtle distinctions and real-time labeling.

Digital Interventions: The critical components, as defined by Wang et al. (2024), are contextual cues, reward mechanisms, timing strategies, and personalization. However, most studies examine only short-term outcomes.

Research Gap: There is no previous work that integrates emotion-aware tracking with computational habit modeling while implementing privacy-preserving architecture.

3. METHODOLOGY

3.1 System Architecture

Technology Stack:

React 18 for UI

IndexedDB via Dexie.js for storage

Recharts for visualization

Offline-First Design:

All data stays on-device and doesn't have privacy risks via cloud storage.

Habit Strength Calculation:

$HS_{t+1} = HS_t - HS_t \times 0.175 + (1 - HS_t) \times Beh_t \times Cue_t \times 0.20$

Parameters from Zhang et al.'s empirical validation.

3.2 Core Features

Habit Creation: Users define habits with name, emoji, color, difficulty, and notes.

Daily Check-In (3-Tap Workflow):

In this step, choose a habit from the list.

Choose emotional state among nine choices:

Valence: Happy, Neutral , Sad, Frustrated

Energy: Confident ; Anxious ; Tired ; Sleepy

Physical: Sick

Confirm completion

Analytics Dashboard: Habit strength visualization by computational model Streak tracking for motivation Emotional pattern correlation (completion rates by mood) Temporal analysis: daily, weekly, monthly patterns

3.3 Privacy Design

Data never leaves a user's device. Application never sends data off the device, analyzes in the cloud or shares with any third party. Does not use clinical language or make diagnostic claims.

4. IMPLIMENTATION

4.1 Database Operations

The basic schema is composed of two main stores: the habits store, which holds habit metadata (name, emoji, color, difficulty, date created), and the completions store, which records every completion of each habit, including the timestamp and emotional state. The computation of Habit Strength is done in the background with empirically validated parameters: HDP = 0.175, HGP = 0.20; get the current strength of a habit and then apply the computational formula, before updating the value in the database.

4.2 Analytics Engine

Groups completions by emotion, calculates success percentages, identifies patterns, and generates visualizations. Displays habit strength progression toward automaticity.

5. APPLICATIONS

Target Users:

Students: Track study habits with emotional productivity correlations

Professionals: Track the work-life balance with regard to their levels of stress/energy.

Health Enthusiasts: Correlate workouts with motivation states

Privacy-aware users: Full control over data on-device

Example Situation:

Student learns that when confident, 85% study completion occurs, whereas when anxious, only 40% does; this enables strategic scheduling.

Professional discovers 90% successful workouts when energized versus 70% failures when tired; uncovers optimal morning exercise timing

Individual sees habit strength gradually increasing despite occasional misses, unlike simple streaks that reset to zero.

6. EVALUATION AND DISCUSSION

6.1 Advantages

Over Simple Tracking: Distinguishes real habits formed from prompted behaviors; informs you when the interventions could be reduced; psychologically enlightening beyond mere statistics.

Compared to self-reports, it: eliminates periodic questionnaires, memory bias, and social desirability effects, while giving continuous assessment.

Emotional Integration: Allows for pattern recognition not achievable with completion data alone.

6.2 Limitations

No Empirical Validation: Requires formal user studies measuring effectiveness

Context Simplification: Assume a constant context, Cue_t = 1

Self-report emotions: do not always reflect true emotional experience.

Limited social features: no accountability or group challenges

Storage Limitations: Device limits can be approached by long-term data accumulation.

6.3 Contributions

Theoretical: Positions emotional intelligence at the core of habit tracking; applies computational models to personal behavior change.

Practical: Provides functional tool with actionable insights; sophisticated analytics without compromising privacy.

Methodological: Proves that offline-first architecture can deliver cloud-comparable analytics; provides blueprint for future systems.

7. FUTURE WORK

Adaptive Learning: Machine learning to optimize HDP/HGP for individuals Context-Aware Modeling: Keep track of several contexts per habit Multimodal Recognition: Fuse wearable physiological signals Longitudinal Studies: Controlled 90+ day validation studies Predictive Interventions: Reminders based on habit strength Cross-Cultural Validation: Testing universal emoji representation 8. CONCLUSION Habitly combines computational habit modeling with the capture of real-time emotional context through an intuitive emoji-based interface. Offline-first architecture ensures complete privacy while delivering sophisticated analytics that correlate emotional patterns with habit success. The 3-tap workflow addresses sustained engagement challenges by minimizing friction. Computed habit strength provides more meaningful progress indicators than simple streaks, distinguishing genuine habit formation from temporary compliance. Contributions include establishing emotional intelligence as one of the core aspects of habit tracking, showing that privacy-preserving architecture can deliver sophisticated analytics, and providing functional tools that translate such complex concepts to the most accessible interfaces. Future work will focus on longitudinal empirical validation, adaptive learning of parameters, and multi-modal emotion recognition with adherence to the privacy core principles.

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